DETERMINING CAPITAL ADEQUACY FOR A COMMUNITY BANK'S AGRICULTURAL LOAN PORTFOLIO

by

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B.A., Chadron State College, 2011

A THESIS

Submitted in partial fulfillment of the requirements

for the degree

MASTER OF AGRIBUSINESS

Department of Agricultural Economics

College of Agriculture

KANSAS STATE UNIVERSITY

Manhattan, Kansas

2015

Approved by:

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ABSTRACT

As the recent financial crisis brought to light, the ability of commercial banks to quantify and better manage risk in their loan portfolios is paramount to their continued success and viability. Assessing, managing, and retaining capital is now a larger issue than ever given this event as well as the advent of the Basel III Accord.

Pinnacle Bancorp is a community banking organization headquartered in Omaha, Nebraska with roughly $8.6 billion in assets. The company is also one of the largest agricultural lenders in the country and the largest agricultural lender among traditional community banks. Given the ominous outlook heading into 2016 for agricultural producers from lower projected net incomes and increased borrowing costs following Federal Reserve action on the Fed Funds Rate, many banks worry about the increased likelihood of default for agricultural producers. The objective of this thesis is to determine the adequacy of Pinnacle Bank's equity capital relative to the agricultural loan portfolio.

This process begins by employing binary logit regression in an effort to determine the probability of default for the bank's agricultural loan portfolio. With default likelihood quantified, efforts are then made to determine the bank's credit value-at-risk at various solvency levels. These figures are then compared to current capital levels in order to determine the adequacy of bank capital as measured by five key regulatory ratios ultimately imposed by Basel III. Finally, recommendations are made to management as to the adequacy of bank capital relative to the agricultural loan portfolio and any future efforts that need to be made in order to determine and ensure the adequacy of bank capital for the entire loan portfolio.

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ACKNOWLEDGMENTS

First and foremost I need to thank my wife for all the support and encouragement throughout my time in the MAB program. Without your willingness to tend to sick and grumpy kids while I was in lectures or working on homework, I would never have completed this program. I also owe a great amount of gratitude to my parents for laying the foundation necessary for this educational achievement.

Thank you to Randy Hupp for encouraging me to start this pursuit of graduate-level education and Brad Bauer for continuing that encouragement. To everyone else at Pinnacle Bank and Pinnacle Bancorp who helped me obtain the data used in this analysis, discussed invigorating topics such as regulatory capital ratios, and provided encouragement, thank you.

Thanks to the MAB faculty for all of your knowledge, patience, and enthusiasm. Specifically, thank you to Deborah Kohl and Mary Bowen. The two of you were instrumental in my ability to complete this program in a timely manner. Your flexibility and dedication are greatly appreciated and this program would not function without you.

Finally, thank you to my thesis committee: Brian Briggeman, Christine Wilson, and Sean Fox. Dr. Briggeman, your patience, wisdom, and candor were key to the effective completion of this thesis. Additional thanks go to Dr. Fox, whom without I would have never understood – nor been able to pronounce – heteroskedasticity. Thank you to Dr. Wilson for your encouragement throughout this past year as well as your willingness to share your industry specific knowledge.

CHAPTER I: INTRODUCTION

Following the “Great Recession” and the subsequent advent of the Basel III Accord, the need for financial institutions to quantify risk increased dramatically. There also came about an urgent need to ensure adequate amounts of bank capital as well as to assess the quality of bank capital. For many community banks with loan portfolios concentrated in agricultural lending, this need is even more pronounced given the ominous 2015 and short term outlook for lower net farm incomes. Further, the near term expectation is for the Federal Reserve to begin increasing interest rates through the Federal Funds Rate.

Pinnacle Bancorp is a community banking organization subject to these challenges. While the bank’s portfolio is well diversified relative to many community banking institutions, it is also one of the nation’s largest agricultural lenders (American Bankers Association 2015). As such, efforts need to be made in order to determine the adequacy of bank capital following the full implementation of Basel III capital requirements by the FDIC.

The objective of this thesis is to analyze Pinnacle Bank’s loan portfolio and associated customer financial data in an effort to assess the adequacy of bank capital relative to the bank’s agricultural loan portfolio. To do this, the portfolio’s probability of default will need to be calculated and understood. After that, steps can be taken to assess the portfolio’s credit value-at-risk and then compare that risk to the bank’s current capital accounts in order to determine the adequacy of capital.

The thesis will proceed as follows: Chapter II of this thesis contains the literature review. Chapter III then looks at the theoretical model that serves as the basis for the thesis. Chapter IV is the methodology section which reviews the collection, selection, and scope of the data as well as defining the various variables and figures used in the analysis. Chapter V reports the findings of the study and interprets the results. Lastly, Chapter VI discusses the conclusions on credit value-at-risk and capital adequacy from the analysis, reports on the limitations of the study, and provides suggestions for future research on the topic as well as improvements for future analysis.

CHAPTER II: LITERATURE REVIEW

2.1 Commercial Bank Loan Portfolio Composition and Allocation

One of the ultimate goals of any bank management team is to allocate capital in the most efficient and effective manner possible. In commercial banking, this means determining the ideal composition of the bank's loan portfolio and then lending funds and purchasing securities in order to optimize this composition. Management will then adjust these allocations as risk tolerances change and as dictated by market forces and regulators.

Commercial bank loan portfolios are comprised of 10 broad categories as reported on Schedule RC-C Part I of the Call Report. The major categories among these are loans secured by real estate, loans to finance agricultural production, commercial and industrial loans, and loans to individuals for personal expenditures. Loans to agriculture make up a significant portion of commercial banks' loan portfolios. According to Call Report data from 1976-2003, agricultural loans make up on average 13.4% of loan portfolios for all commercial banks (Zarutskie 2013). While this is by no means the largest portion of bank loan portfolios – real-estate backed loans (including farmland) accounted for 45.3% in the same analysis – agriculture is a significant player in the portfolio composition of commercial banks.

Moreover, the bank to be analyzed in this thesis is one of the largest agricultural lenders in the country. As of the Second Quarter 2015, Pinnacle Bank is the eighth largest farm lender by dollar volume in the United States amongst commercial banks consolidated at the Bancorp level with $1.59 billion in total farm loans (American Bankers Association 2015). This represents 27.6% of the bank's entire loan portfolio. Out of the top 10 lenders by this measure, that concentration is exceeded only by Rabobank and John Deere Financial, lenders catered specifically to the agricultural industry.

2.2 Perceived Bank Loan Portfolio Risk and Capital Requirements

There are a number of factors that influence how a commercial bank determines the proper allocation for its loan portfolio. These factors differ from bank to bank, but common among them are risk aversion and capital requirements (both internal and external). A great deal of research has been completed on both the perceived levels of bank loan portfolio risk and capital requirements, as well as their interconnectivity. As noted by Jokipii and Milne (2011), though, this relationship is viewed rather ambiguously by the theoretical literature that currently exists.

Shim (2013) states that for forward-looking banks, it is likely that both loan portfolios and capital buffers will expand during times of GDP growth. He theorizes that the buildup of capital will occur for two reasons. First, the increased lending brings with it increased risk. Consequently, the prudent management team will build up capital buffers to account for this increase in perceived risk. Secondly, it is more cost effective to build up capital buffers during economic booms than it is in declines. This is due to the fact that increasing capital through profitability (i.e., earnings retained and not used to issue dividends or repurchase shares) is likely much cheaper than raising capital through external channels in a depressed economy.

However, the research shows that most banks do not behave in this forward-looking fashion. Instead, they tend to decrease capital buffers in periods of economic growth and increase them in down cycles. As banks expand their lending during stages of economic strength, they tend to underestimate their risk exposure, thus leading to inadequate capital buffers when markets do ultimately contract (Shim 2013).

This relationship can be further broken down by the degree of bank capitalization. Research shows that well capitalized banks, at least in the short term, see a positive relationship between capital buffers and risk – increasing loan portfolio risk when capital increases. On the other hand, banks with smaller capital buffers see a negative relationship – rebuilding their buffers by simultaneously raising capital and lowering risk (Jokipii and Milne 2011).

2.3 Borrower Default, Probability of Default, and Bank Capital Implications

A fair amount of recent work has been completed on probability of default (PD) as it relates to agricultural lending. Default can be defined in many ways and how it is defined is critical to any analysis. Default is often deemed to have occurred if one of the four following parameters are met: borrower files bankruptcy, loan becomes 90 days or more past due, loan is placed on non-accrual status, or any portion of the debt is charged off (Schuermann 2004). The literature, though, demonstrates that while the delinquency definition is the most common, it is certainly not the only one employed.

In one study of PD, Jacobson and Roszbach (2003) defined default as loans submitted to a debt collection agency. Due to a lack of loan data, Katchova and Barry (2005) approached the issue of PD differently, using producer balance sheets to define default as credits with debt-to-asset ratios exceeding 100%. Meanwhile, Featherstone, Roessler, and Barry (2006) and Jouault and Featherstone (2011), among others, use the 90 day delinquency definition of default. According to the Basel Committee on Banking Supervision, default is defined as occurring when a credit "is past due more than 90 days on any material credit obligation" or "the bank considers that the [borrower] is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank" (2002, 78).

The reasons for default are numerous. Low levels of liquidity and high levels of leverage are standard reasons for default because they raise the PD. Many other issues, both quantitative and qualitative, can also impact a credit's risk of default. Odeh, et. al. (2011) found low working capital to be the most consistent predictor of default likelihood. This stands to reason, especially given the delinquency definition of default, since low-to-inverted working capital would mean a borrower will have a tough time servicing debt in the short term. In another study, though, owner equity percentage was found to have a greater impact on PD relative to working capital and repayment capacity (Featherstone, Roessler and Barry 2006). In two separate studies, loan commitment size has been shown to not be statistically significant in predicting PD (Featherstone, Roessler and Barry 2006; Jouault and Featherstone 2011).

2.4 Credit Risk, Credit Risk Models, and Agricultural Lending

Agricultural lending brings with it some unique challenges in regards to properly managing bank capital. One of the most important challenges it presents is the correlation between farms' financial performance, especially given the relatively small geographic areas in which many agricultural lenders operate (Katchova and Barry 2005). It is imperative that banks are able to quantify credit risk if they are to properly allocate and manage capital.

Credit risk, as defined by Barry, "is the possibility of default by borrowers in meeting repayment obligations" (2001, 104). With the advent of the Basel II Accord, greater emphasis was placed on management being able to quantify and control credit risk using methodologies such as value-at-risk (VaR) in order to determine the level of capital necessary to properly backstop risk (Katchova and Barry 2005). Basel III mainly focused on increasing levels of capital and liquidity as well as capital quality, which increases the need for banks to properly and accurately identify and model credit risk (Samuels 2012).

Many models have been proposed in the literature for analyzing credit risk in a manner that satisfies regulators' capital requirements. Jacobson and Roszbach (2003), for instance, employed a bivariate probit model to estimate credit risk for a segment of a Swedish bank's consumer revolving loan portfolio. They then employed VaR methodology to demonstrate how switching from a credit-scoring model to a default-risk-based decision model would limit default losses and create greater efficiencies within the whole portfolio. Barry, Escalante, and Ellinger (2002) studied migration among various risk ratings by farm businesses as a means of quantifying risk for capital management considerations. Jouault and Featherstone (2011) utilized a binomial logit regression in their analysis of PD in a French bank's agricultural portfolio in order to test the effectiveness of two separate models used by the bank. Katchova and Barry (2005), meanwhile, developed a model specifically catered to agricultural lenders by using distance-to-default methodology via Merton's option pricing model to determine credit value-at-risk (CVaR).

2.5 Interest Rates and Commodity Prices Influence on Credit Quality

On December 16, 2008 the Federal Open Market Committee (FOMC) reached the zero-bound for the federal funds rate after a year of rapid lowering (Federal Reserve Bank of New York 2010). This action had profound implications for agriculture as well as the credit worthiness of industry members. While the bulk of the world was suffering from the worst financial crisis in decades, agriculture was experiencing prolonged highs like never before. Lower interest rates decreased borrowing costs, thereby bolstering farmland values via lower capitalization rates. Credit quality was also bolstered by surging commodity prices. Significant weather events as well as massive global demand shifts caused a spike in commodity prices that boosted net farm income to unprecedented levels. With increased profitability, lower leverage due to farm real estate appreciation, and lower interest costs, farm financial statements, and thus credit worthiness, strengthened substantially.

When the FOMC eventually decides to raise the Federal Funds Rate, thereby increasing short-term operating rates, borrowing costs will increase, which may stress agricultural producers' cash flows. Couple this with a decrease in commodity prices (namely corn, soybeans, wheat, feeder cattle, and live cattle), and credit quality will certainly deteriorate due to decreased profitability and tighter repayment ratios. Furthermore, if rising interest rates prove to have a negative impact on farmland values as theory would suggest and as demonstrated by Schurle, et. al. (2012), credit quality could weaken further due to an increase in leverage and lowering of collateral margins.

The question then lingers, what impact will these events have on PD? In a study of a Farm Credit System association's portfolio over a seven year time period, Zollinger found that "average [probability of default] ratings held relatively consistent over the years with any fluctuation driven largely by commodity price cycles" (2015, 45). Naturally, we would anticipate that PD would increase given the deleterious effects decreasing commodity prices and increasing interest rates, both individually and in tandem, would have on producers' financials. Working capital will drop with crop inventory, growing crops, and market livestock all being worth less, ceteris paribus. An increase in accrued interest stemming from an increase in operating rates would only serve to further weaken liquidity in this situation. As mentioned earlier, low levels of working capital have been found to be a consistent predictor of default (Odeh, et al. 2011). Owner equity, which has also been shown to be a leading indicator of default, would decline further given these items, as well as lower real estate valuations (Featherstone, Roessler and Barry 2006).

CHAPTER III: MODELING LOAN DEFAULTS

3.1 Introduction

In commercial banking, loan defaults are mitigated by maintaining adequate capital levels. High levels of capital and large capital buffers not only help to satisfy regulatory agencies, but they also provide commercial banks with the flexibility necessary to enhance yield through loans and investments. The prudent management team will ensure the bank has adequate capital levels because it is ultimately their best resource for effectively backstopping credit risk. In order to limit capital at risk, management must understand the risks facing their portfolio and have a plan in place to defend against said risk.

A key determinant in assessing capital adequacy is quantifying losses, or the credit value-at-risk (CVaR). In relation to a loan portfolio, CVaR is comprised of two distinct elements, each of which can be analyzed separately. These two elements are expected loss (EL) and unexpected loss (UL) (Katchova and Barry 2005). EL can be expressed as a function of probability of default (PD) and loss given default (LGD). Meanwhile, UL is a function of management's risk tolerance, portfolio risk, and LGD (Katchova and Barry 2005).

3.2 Model Structure

3.2.1 Expected Loss (EL)

As defined by Barry (2001), PD "indicates how frequently a loss may occur." In order to determine the portfolio's PD, each individual loan's PD must first be calculated. Binomial logit regression is employed to achieve this end. According to Studenmund (2011, 441-442), logit regression uses maximum likelihood to "choose coefficient estimates that maximize the likelihood of the sample data being observed." Moreover, binomial logit regression avoids the unboundedness problem seen in the linear probability model (Studenmund 2011, 440).

The model will take the following form based on a borrower's leverage, liquidity, repayment, and profitability at origination as well as their primary agricultural production type:

3.1 $logit(PD_i) = \beta_0 + \beta_1 D/E_i + \beta_2 CR_i + \beta_3 CDRC_i + \beta_4 ROE_i + \beta_5 COW_i + \varepsilon$

where D/E_i is a given borrower's Debt-to-Equity ratio at loan origination, CR_i is the borrower's Current Ratio at loan origination, $CDRC_i$ is the borrower's Capital Debt Repayment Capacity at loan origination, ROE_i is the borrower's Return on Equity at origination, and COW_i is a dummy variable which takes a value of 1 if the borrower is primarily a livestock producer and 0 if primarily a grain producer.

After exponentiating the log odds scale as follows:

3.2 $\exp[logit(PD_i)] = \exp(\beta_0 + \beta_1 D/E_i + \beta_2 CR_i + \beta_3 CDRC_i + \beta_4 ROE_i + \beta_5 COW_i)$

we can finally find the actual individual PD:

3.3 $PD_i = 1 - \frac{1}{1 + \exp(\beta_0 + \beta_1 D/E_i + \beta_2 CR_i + \beta_3 CDRC_i + \beta_4 ROE_i + \beta_5 COW_i)}.$

With each loan's PD_i determined, the portfolio's PD can be determined by weighting each individual loan's commitment as a share of the entire portfolio using the following equation:

3.4 $w_i = \frac{LC_i}{\sum_{i=1}^{N} LC_i}$

where LC_i is the individual loan's commitment at origination (total dollar exposure approved by the bank for that particular loan) and then summing across the portfolio:

3.5 $PD_P = \sum_{i=1}^{n} w_i PD_i$

With PD_p determined, the next step in calculating *EL* for the portfolio is to determine LGD_p. Barry (2001) states that LGD "indicates the severity of default." Like PD, LGD first needs to be calculated for each i^{th} loan. The Foundation IRB Approach in Basel II specifies LGD_i rates of 45% and 75% to be used for unsecured, senior debt and subordinated debt, respectively, while collateralized debt is to be based on a simple calculation of collateral margin (Basel Committee on Banking Supervision 2002, 50). At the individual loan level, LGD_i for collateralized debt can be simply calculated as:

3.6 $LGD_i = LC_i * (1 - RR_i)$

where LC_i is the bank's commitment amount at origination for a given defaulted farm and RR_i is a specified recovery rate based upon collateral. LGD_i for a non-defaulted farm will be 0.00%.

After determining each defaulted farm's LGD, the portfolio's average LGD figure can be calculated by weighting each loan by the debt in default.

EL is expressed in dollar terms by employing the following formula:

3.7 $EL = PD_P * LGD_P * EAD$

where *EAD* is the portfolio's exposure at default and is calculated as the sum of the agricultural loan portfolio's outstanding principal and unutilized commitment on a certain day along with any expenses incurred in collection.

3.2.2 Unexpected Loss (UL)

With portfolio risk being a function of the number of observations within a portfolio and default correlations amongst borrowers within the portfolio, risk should decrease as the number of observations within a portfolio increases, assuming default correlations remain constant (Katchova and Barry 2005). Portfolio risk can be quantified by calculating the standard deviation of default for a portfolio of farms.

Following Katchova and Barry (2005), with default being a binary variable, the average standard deviation of default for a loan can be expressed as:

3.8 $SD = \sqrt{PD_P(1 - PD_P)}$.

As mentioned above, standard deviation of default for a portfolio can be determined based upon the weight of a farm relative to the portfolio and the correlation of default between borrowers in the portfolio. However, because calculating default correlations between borrowers requires repeated default observations, many studies substitute asset return correlations for default correlations (Katchova and Barry 2005). Assuming a uniform distribution, standard deviation of default for a portfolio can be calculated as follows:

3.9 $SD_P = SD\sqrt{rc + \frac{1-rc}{N}}$

where *rc* is the average asset return correlation between farms and *N* is the number of loans in the portfolio (Katchova and Barry 2005).

A probability can now be specified for determining the specific risk tolerance of management. The product of Equation 3.9, the critical value associated with the chosen probability, LGD_p, and *EAD* will express *UL(α)* in dollar terms. That is:

3.10 $UL(\alpha) = N^{-1}(\alpha) * SD_P * LGD_P * EAD$

where $N^{-1}(\alpha)$ is the critical value associated with the specified probability in a normal distribution.

3.2.3 Credit Value-at-Risk (CVaR)

As aforementioned, CVaR is an attempt to quantify losses in an effort to enable management to analyze the adequacy of bank capital. CVaR expresses the level of losses that will exceed a specified probability *α* which is defined by management based on their risk tolerance. Thus, as *α* becomes smaller (moves closer to 0), CVaR will increase. Once

EL and *UL*(α) have been identified, *CVaR (1-α)* is a rather simple, albeit critical, calculation:

3.11 $CVaR(1-\alpha) = EL + UL(\alpha).$

CHAPTER IV: DATA

4.1 Objective

The objective of this thesis is to quantify risk in Pinnacle Bank's agricultural loan portfolio in an effort to determine the adequacy of bank capital in light of developments with the Basel Accords. This need is even more stressed given the ominous outlook for community banks heavy in agricultural lending stemming from the strong possibility of higher interest rates and declining commodity prices.

4.2 Data Collection, Selection, and Scope

Data were obtained from Pinnacle Bancorp's loan accounting database and lending software. While the Bancorp is comprised of four charters, only the Pinnacle Bank charter comprised of Nebraska, Kansas, and Missouri banks was included in the analysis. The loan data and financial data are stored in two separate systems. Data were pulled from each system and then manually paired.

The original loan dataset contained a total of 7,980 unique observations. The dataset included the following information: note number, portfolio number, original note date, original maturity date, collateral code, class code, original commitment amount, months to maturity at origination, first payment date, times past due over 90 days, times past due 60-89 days, and times past due 30-59 days.

Unfortunately, the loan data only covered loans that were either active or paid off in the 2015 calendar year and no loans originated prior to 2007. As such, 2,873 loans were removed from the dataset as their first payment had either yet to be due or had occurred within the last 90 days, therefore not having the ability to default. Another 79 loans belonging to a recently acquired bank were deleted as there was incomplete historical information available.

The original financial dataset contained a total of 6,288 unique observations covering 1,130 different customers. Financial data included the following information: customer name, customer identifier, portfolio number, NAICS code, beginning balance sheet date, ending balance sheet date, beginning equity value, ending equity value, earned equity value, CDRC%, balance sheet date, current ratio, and debt-to-equity ratio. Any customer who was missing any of the above information, were not pulled into the dataset. Thus, a customer whose NAICS code was not input by the loan officer or credit analyst is not included in the study. A return on equity (*ROE*) category was added to the dataset by taking the earned equity figure divided by the average of the beginning and ending equity values.

In the process of consolidating the loan and financial datasets, 2,772 loans belonged to customers who did not have financial information stored in the financial system and were consequently deleted from the dataset. Another 439 loans did not have financial data at origination and were removed. Finally, 47 loans were removed due to missing ratios.

After the two datasets were consolidated and culled, 1,770 unique, consolidated loan observations remained. However, as with any dataset that involves manual input, the potential exists that not all financial data were entered or calculated correctly. In looking at key statistics of the dataset, there were obvious outliers. Following Featherstone, Roessler, and Barry (2006), any financial ratio exceeding three standard deviations above or below the mean was adjusted back so as not to exceed that limit. For example, if a given ratio for a borrower was -10 in the original data set, the mean was 0.5, and the standard deviation was 1, the figure of -10 would be adjusted to -2.5. This approach should capture more than 99% of the observations if the dataset is normally distributed. The intent of this method is to not eliminate any outlying observations as the potential exists that they were defaulting loans.

Adjustments were made for the four financial ratios included in the study: return on average equity (*ROE*), capital debt repayment capacity (*CDRC*), current ratio (*CR*), and debt-to-equity (*D/E*). With all the ratios, less than two percent (2%) of the figures were adjusted. Table 4.1 below outlines the adjustment thresholds used for each of the four ratios. There were five loans that had negative *D/E* ratios due to the borrower showing a negative net worth. These five loans were adjusted to the upper threshold as the negative *D/E* mark would skew the ratios when in reality the borrower is highly leveraged.

Table 4.1: Adjustments to Dataset Variables Used in Probability of Default Calculation

	Mean	Standard Deviation (SD)	Mean - 3xSD	Mean + 3xSD
Return on Equity	0.102	0.266	-0.696	0.901
Capital Debt Repayment Capacity	2.915	7.509	-19.611	25.440
Current Ratio	3.425	9.576	-25.303	32.153
Debt-to-Equity	0.731	1.089	-2.534	3.997

Table 4.2 below shows key statistics for the dataset after the above described adjustments were made.

Table 4.2: Distribution of Variables Used in Probability of Default Calculation (All Loans)

	Mean	Median	Standard Deviation
Default 90 Days	0.007	0	0.082
Default 60 Days	0.018	0	0.133
Default 30 Days	0.118	0	0.322
Return on Equity	0.096	0.066	0.207
Capital Debt Repayment Capacity	2.720	1.480	5.064
Current Ratio	2.962	1.420	4.935
Debt-to-Equity	0.712	0.510	0.734
Livestock Producer	0.489	0	0.500
Grain Producer	0.000	0	0.000

The distributions of each adjusted financial ratio are shown in the histogram figures below.

Figure 4.1: Distribution (%) of Return on Equity Variable

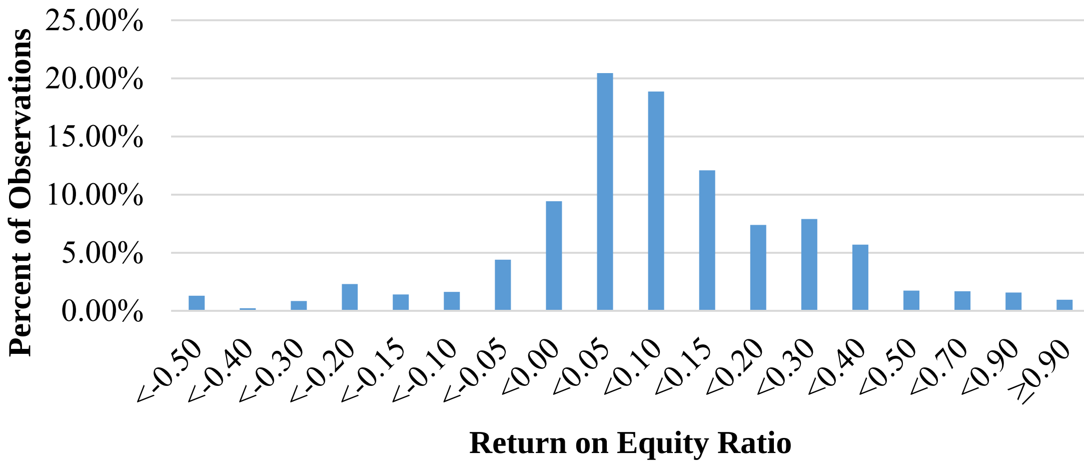


Figure 4.2: Distribution (%) of Capital Debt Repayment Capacity Variable

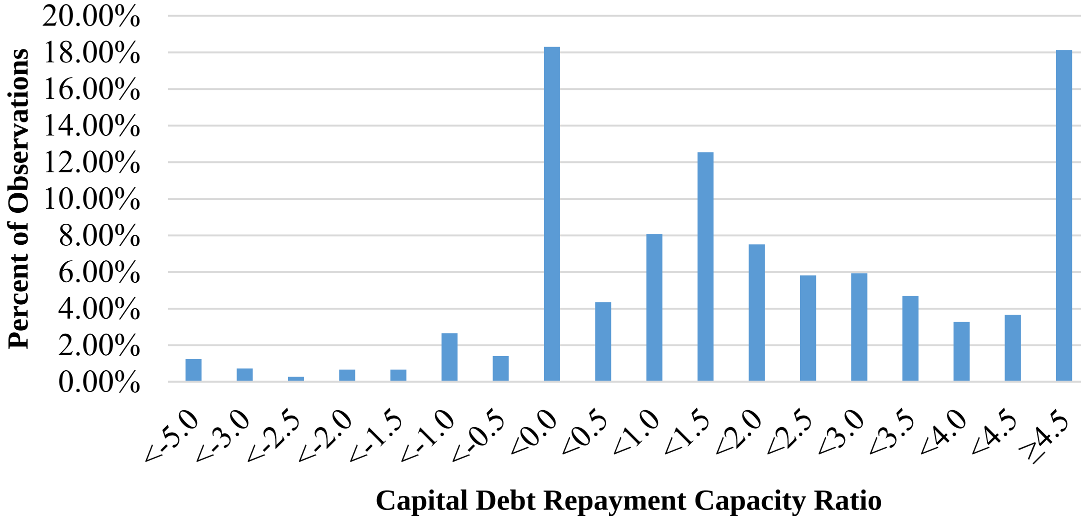


Figure 4.3: Distribution (%) of Current Ratio Variable

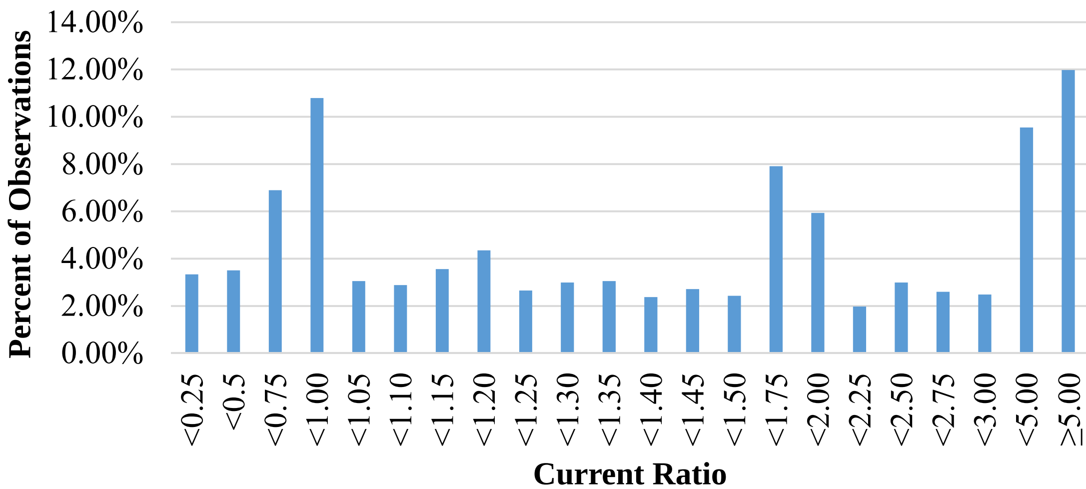
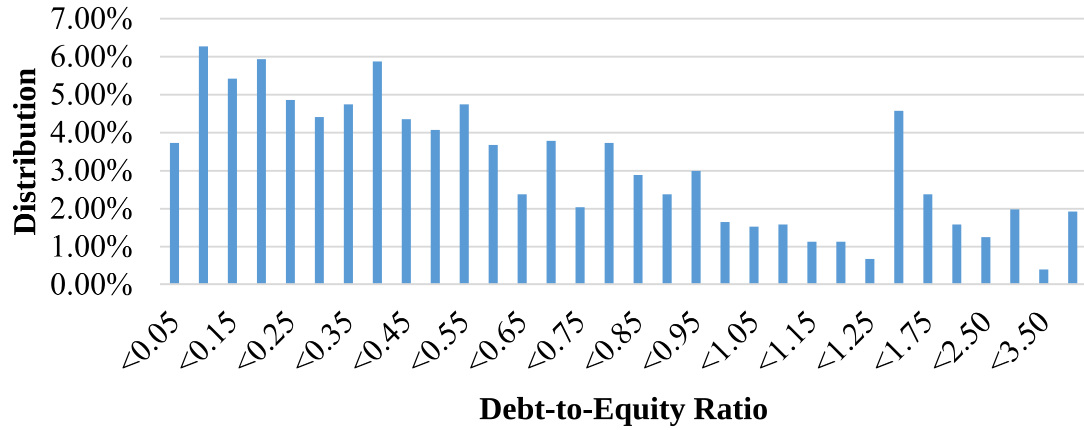
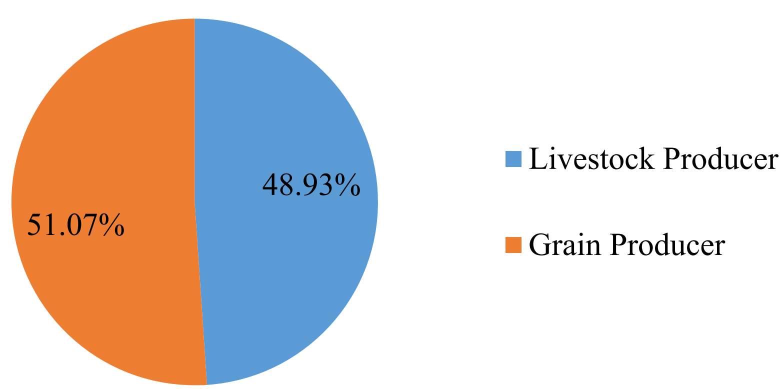


Figure 4.4: Distribution (%) of Debt-to-Equity Variable



As mentioned earlier, borrowers were broadly grouped by producer type as either livestock producers or grain producers. Interestingly enough, the dataset was an almost even split amongst the two industries (Figure 4.5).

Figure 4.5: Distribution of Loans by Industry



As Samuel states (2012, 14), "portfolios that exhibit low rates of default…rarely generate enough internal default data to support robust statistical analysis." However, he goes on to state that there is danger present in applying external data as that data may not encapsulate the true risk characteristic of the bank's portfolio. Moreover, most available default data is centered on portfolios dominated by commercial and real estate loans. With this analysis centered on Pinnacle Bank's agricultural loan portfolio only, there is very little external data available to use in such an analysis before even taking into consideration the risk characteristic issue. As such, the bank's internal data is used while fully recognizing the issue of low default rates on the analysis.

4.3 Regression Variables

The variables used in Equation 3.1 are further described below:

4.3.1 Dependent Variable

Probability of Default (PD): Represents whether or not the loan defaulted during the specified time period. Takes a value of 1 if the loan defaulted at any point in time and a value of 0 if it did not.

4.3.2 Independent Variables

Debt-to-Equity Ratio (D/E): Calculated by taking a borrower's total debt and dividing by their total equity. This ratio is used to represent the borrower's overall leverage at origination. A borrower with greater equity has a greater chance to use that equity to avoid a default situation. As such, it is expected that the regression coefficient will be positive as higher leverage should indicate a higher likelihood of default.

Current Ratio (CR): Calculated by taking a borrower's current assets and dividing by their current liabilities. This ratio is used to represent the borrower's liquidity at origination. A ratio of less than 1.00 indicates a borrower is illiquid. It is expected that the regression coefficient will be negative as higher levels of liquidity should be associated with lower levels of default since more cash is available to service debt and thus avoid default.

Capital Debt Repayment Capacity (CDRC): Calculated by taking the sum of earned equity change, term interest, and depreciation and dividing by the sum of term interest and term principal. This ratio is used to represent the borrower's repayment capacity at origination. It is expected that the regression coefficient will be negative as greater repayment capacity should logically limit PD. However, the potential exists that this metric will not have a great degree of significance due to the fact that credits with no term debt will have figures of 0.00.

Return on Average Equity (ROE): Calculated by taking the earned equity value and dividing by the average of beginning and ending equity. This ratio is used to represent the borrower's profitability at origination. It is expected that the regression coefficient will be negative as greater profitability should mean a lesser chance of default.

Industry (COW): Represents the borrower's primary source of agricultural production. Takes a value of 1 if the borrower is primarily a livestock producer and 0 if primarily a grain producer (base case). It is unknown what to expect for the sign of this regression coefficient as it is included to investigate the effect of industry on PD.

4.4 Loss Given Default (LGD)

As described in Equation 3.6, the recovery rate (RR_i) will be based upon collateral. However, obtaining correct collateral values for each loan is extremely difficult given the dataset due to cross-collateralization. Moody's data from 1988-2Q 2009 shows ultimate discounted recovery rates for secured bank debt at 85.63% and unsecured bank debt at 56.34% (Altman 2011). The ultimate discounted recovery rates demonstrate the bank's net recovery after fees incurred in liquidation. This unsecured recovery rate closely mirrors Basel II's required loss rate of 45% (1-0.5634). Therefore, loss rates on senior, collateralized loans in the dataset will be estimated at 15% (1-0.8563, rounded up). Out of all 1,770 loan observations in the dataset, only six were unsecured and 11 held subordinated collateral positions.

4.5 Unexpected Loss (UL) Probabilities

Due to difficulties in determining asset return correlations within the given dataset, the figure estimated by Katchova and Barry (2005) of 10.050% in their analysis of Illinois farms will be utilized to determine the standard deviation of default for the portfolio.

Unexpected losses will be calculated at three different levels: 5%, 1%, and 0.03%. The critical values, $N^{-1}(\alpha)$, associated with these loss levels are 1.6449, 2.3263, and 3.4316, respectively. The 0.03% loss level is employed due to the fact that S&P's standard for an AA rating is a mean default rate of 0.03%, a goal of many larger financial institutions (Katchova and Barry 2005). Moreover, an analysis of 17 major banks in 2011 showed 45% used the 99.97% confidence interval in their economic models, by far the most common (Mehta, et al. 2012). This was even more pronounced amongst regional banks, relative to global and investment-focused banks.

CHAPTER V: LOAN DEFAULT RESULTS AND CAPITAL ANALYSIS

5.1 Introduction

In this chapter, the results of the regression model outlined in Chapters III and IV are reported and analyzed. Binary logit regression will be utilized to predict probability of default (PD) within the portfolio. The results of this regression will be used to determine PD for the entire agricultural loan portfolio which will then be added together with other metrics to determine the Credit Value-at-Risk (CVaR) for the portfolio at various levels of significance. While the main objective will be to determine the CVaR using a 90 day past due definition of default as specified by Basel II (2002, 78), three levels of default (90 days, 60 days, and 30 days past due) will ultimately be analyzed in an attempt to stress the portfolio's capital requirements. Using the model's predicted default probabilities, the portfolio's CVaR is then calculated at three different solvency rates.

After running the models and determining *CVaR (1-α)*, predicted losses are taken from current capital levels to assess the effects of default on key regulatory capital ratios. The updated ratios are then compared to interagency recommendations following full implementation of Basel III to assess the adequacy of bank capital.

5.2 Analysis

In all, the loans in the dataset did not realize many defaults over the time period studied. This is partially assumed to be a product of Pinnacle Bank's relatively conservative culture and strive for high quality assets. Additionally, the years covered in this dataset (2007-2015) were relatively good years for agriculture. Table 5.1 provides a snapshot of the defaulted loans as a proportion of the entire loan dataset of 1,770.

Table 5.1: Loans in Default

	Defaulting Loans	Defaulting Loans (%)	Volume Defaulted	Volume Defaulted (%)
90 Day Default	12	0.678%	$ 3,375,078.00	0.747%
60 Day Default	32	1.808%	$ 10,236,504.50	2.266%
30 Day Default	208	11.751%	$ 53,820,560.48	11.912%

Tables 5.2 and 5.3 below demonstrate the distribution statistics for the variables included in the regression model, broken down into defaulting loans and non-defaulting loans.

Table 5.2: Distribution of Variables Used in Probability of Default Calculation (Non-Defaulted Loans Only)

	Mean	Median	Standard Deviation
Default 90 Days	0.000	0	0.000
Default 60 Days	0.011	0	0.106
Default 30 Days	0.111	0	0.315
Return on Equity	0.097	0.066	0.207
Capital Debt Repayment Capacity	2.736	1.480	5.076
Current Ratio	2.978	1.420	4.948
Debt-to-Equity	0.701	0.505	0.714
Livestock Producer	0.490	0	0.500
Grain Producer	0.510	1	0.500

Table 5.3: Distribution of Variables Used in Probability of Default Calculation (90 Day Defaulted Loans Only)

	Mean	Median	Standard Deviation
Default 90 Days	1.000	1	0.000
Default 60 Days	1.000	1	0.000
Default 30 Days	1.000	1	0.000
Return on Equity	0.001	0.083	0.241
Capital Debt Repayment Capacity	0.464	-0.280	1.630
Current Ratio	0.669	0.730	0.319
Debt-to-Equity	2.377	1.900	1.496
Livestock Producer	0.417	0	0.515
Grain Producer	0.583	1	0.515

5.2.1 Results Using 90 Day Definition of Default

The regression results below in Table 5.4 show the model using the 90 day definition of default. The model shows us that the liquidity and leverage variables at origination are statistically significant at the 1% level using a one-sided hypothesis test. The repayment capacity, profitability, and industry variables are all statistically insignificant. All coefficients had the expected sign, except for *ROE*, which was not statistically significant. After running a correlation test, multicollinearity does not appear to be an issue in the model.

Table 5.4: Logistic Regression Results Using 90 Days Past Due Definition of Default

Variable	Estimated Coefficient	Standard Error	z	P>|z|
Debt-to-Equity	0.921	0.220	4.190	0.000
Current Ratio	-2.019	0.773	-2.610	0.009
Capital Debt Repayment Capacity	-0.006	0.094	-0.060	0.950
Return on Equity	0.160	0.901	0.180	0.859
Livestock Producer	-0.494	0.620	-0.800	0.426
Constant	-3.922	0.881	-4.450	0.000

Goodness of Fit Statistics

Likelihood Ratio Chi^2	Prob > Chi^2	Pseudo R^2
39.416	0.000	0.274

Given the likelihood ratio's chi-square value, the model is statistically significant in predicting loan default. As such, the null hypothesis that β_i for all independent variables is zero is rejected.

The marginal effects of each independent variable are provided below in Table 5.5. The marginal effects show the impact of a one unit change in each independent variable on the overall predicted probability of default, ceteris paribus. As can be seen, a one unit change in *CDRC*, *ROE*, and *COW* has little to no impact on the predicted PD_i. This is not surprising given their statistical insignificance in the model. A one unit change in *D/E* has a more pronounced impact on PD_i relative to the three prior mentioned ratios, though a large figure is still needed to move the needle. *CR* has the largest marginal effect on PD_i in the model, with a one unit change altering PD_i 1.2%. The marginal effect of *D/E* is statistically significant at the 1% level while *CR* is significant at the 5% level. The remaining three marginal effects are all statistically insignificant, just as in the model.

Table 5.5: Marginal Effects Using 90 Days Past Due Definition of Default

Variable	Estimated Marginal Effect	Standard Error	z	P>|z|
Debt-to-Equity	0.006	0.002	3.060	0.002
Current Ratio	-0.012	0.006	-2.240	0.025
Capital Debt Repayment Capacity	0.000	0.001	-0.060	0.950
Return on Equity	0.001	0.006	0.180	0.859
Livestock Producer	-0.003	0.004	-0.790	0.430

After applying Equations 3.1, 3.2, and 3.3 to each individual loan, a two percent cutoff was used to assess the model's ability to predict PD_i. These findings are summarized below in Table 5.6.

Table 5.6: Prediction Results Using 90 Days Past Due Definition of Default

	Loans Correctly Predicted (%)	Loans Correctly Predicted	Actual Loans
All Loans	94.80%	1,678	1,770
Defaulted Loans	58.33%	7	12
Non-Defaulted Loans	95.05%	1,671	1,758

With PD_i determined, Equations 3.4 and 3.5 were employed to determine the portfolio's PD rate. The portfolio's average loss given default (LGD) was next determined using Equation 3.6 and then weighted as described in Section 3.2.1. The product of these two figures is *EL* expressed in percentage terms. To express *EL* in dollar terms, the product was multiplied by *EAD*. *EAD* in this analysis is the sum of Pinnacle Bank's loans secured by farmland and loans to finance agricultural production and other loans to farmers from Schedule RC-C Part I of the 06/30/2015 Call Report as reported by the Federal Financial Institutions Examination Council (FFIEC). The figures calculated from the model are summarized below in Table 5.7.

Table 5.7: Expected Loss Figures Using 90 Days Past Due Definition of Default

Portfolio Probability of Default		0.682%
Portfolio Loss Given Default		15.000%
Portfolio Expected Loss (%)[a]		0.102%
Exposure at Default	$	997,635,000
Portfolio Expected Loss ($)[b]	$	1,019,889.97

[a] PD_p x LGD_p = EL in percentage terms

[b] PD_p x LGD_p x EAD = EL in dollar terms

The next step is to determine the portfolio's UL rate. First, the average standard deviation of default for a loan was calculated using Equation 3.8 resulting in a figure of 8.227%. Next, the standard deviation of default for the portfolio was determined using Equation 3.9 and produced a figure of 2.615%. As aforementioned, $UL(\alpha)$ is calculated at three levels: 5%, 1%, and 0.03%. The product of the critical value associated with these probabilities, LGD_p, and SD_p allows $UL(\alpha)$ to be expressed in percentage terms. Multiplying that figure by the same *EAD* figure mentioned above, gives $UL(\alpha)$ in dollar terms (Equation 3.10). The model's calculated $UL(\alpha)$ figures are summarized below in Table 5.8.

Table 5.8: Unexpected Loss Figures Using 90 Days Past Due Definition of Default

Unexpected Loss 5% (%)		0.645%
Unexpected Loss 5% ($)	$	6,436,368.79
Unexpected Loss 1% (%)		0.912%
Unexpected Loss 1% ($)	$	9,102,635.24
Unexpected Loss 0.03% (%)		1.346%
Unexpected Loss 0.03% ($)	$	13,427,590.20

Finally, *CVaR (1-α)* is determined by summing *EL* and *UL(α)* at each chosen probability (Equation 3.11). These figures are all summarized below in Table 5.9 in both percentage and dollar terms as calculated from the model.

Table 5.9: Credit Value-at-Risk Using 90 Days Past Due Definition of Default

Credit Value-at-Risk 95% (%)		0.747%
Credit Value-at-Risk 95% ($)	$	7,456,258.76
Credit Value-at-Risk 99% (%)		1.015%
Credit Value-at-Risk 99% ($)	$	10,122,525.21
Credit Value-at-Risk 99.97% (%)		1.448%
Credit Value-at-Risk 99.97% ($)	$	14,447,480.17

EL, *UL(α)*, and *CVaR (1-α)* can all be expressed as a percentage of Total Equity Capital and Tier 1 Capital as well. This is demonstrated below in Table 5.10. The Total Equity Capital figure of $418,233,000 and Tier 1 Capital figure of $394,013,000 both come from the same Call Report used to determine *EAD*.

Table 5.10: Loss Figures as % of Capital Using 90 Days Past Due Definition of Default

	As % of Total Equity Capital	As % of Tier 1 Capital
Expected Loss	0.244%	0.259%
Unexpected Loss (5%)	1.539%	1.634%
Credit Value-at-Risk (95%)	1.783%	1.892%
Unexpected Loss (1%)	2.176%	2.310%
Credit Value-at-Risk (99%)	2.420%	2.569%
Unexpected Loss (0.03%)	3.211%	3.408%
Credit Value-at-Risk (99.97%)	3.454%	3.667%

The *CVaR (1-α)* figures represent the total capital needed to protect the bank's expected and unexpected losses in the agricultural loan portfolio at the chosen solvency rates. Thus, according to the model roughly 3.5% of the bank's total equity capital as of 06/30/15 is needed to backstop the bank's losses at the 99.97% solvency rate, a seemingly strong figure given the fact that outstanding agricultural loans made up 33.02% of total loans as of 06/30/2015.

5.2.2 Capital Implications of Losses Using 90 Day Definition of Default

In an effort to analyze the impact of losses to key regulatory capital ratios, the *CVaR (1-α)* figures were subtracted from Common Equity Tier 1 Capital, Tier 1 Capital, and Total Equity Capital. Key capital ratios were then recalculated using the 06/30/2015 Call Report data. These ratios, along with the respective current, recommended, and required figures are included below in Table 5.11. The required figures are the final 2019 capital rules per interagency guidelines following the full adoption of Basel III (Federal Deposit Insurance Corporation 2013). Recommended figures are the required ratio plus the 2.5% capital conservation buffer required in order to have no payout limitations (e.g., dividends) on eligible retained income.

Table 5.11: Loss Effects on Capital Ratios Using 90 Days Past Due Definition of Default

	Common Equity Tier 1 Capital Ratio	Tier 1 Capital Ratio	Total Capital Ratio	Tier 1 Leverage Ratio	Capital Conservation Buffer
Current	11.537%	11.537%	12.790%	9.328%	5.537%
Post-Loss (95%)	11.319%	11.319%	12.571%	9.151%	5.319%
Post-Loss (99%)	11.241%	11.241%	12.493%	9.088%	5.241%
Post-Loss (99.97%)	11.114%	11.114%	12.367%	8.986%	5.114%
Recommended	7.000%	8.500%	10.500%	≥ 5.000%	2.500%
Required	4.500%	6.000%	8.000%	4.000%	0.625%

As can be seen above in Table 5.11, Pinnacle Bank appears to currently be well capitalized with all ratios far exceeding the figures ultimately recommended by the Federal Reserve, FDIC, and OCC in accordance with Basel III. After factoring the calculated *CVaR (1-α)* summarized in Table 5.9 into each of the key regulatory capital ratios' numerators, the bank's capital still appears to be more than sufficient. It should be noted, however, that the *CVaR (1-α)* figures above only cover the agricultural loan portfolio. Agricultural loans only account for roughly 1/3 of the bank's current outstanding loan principal. Thus, further consideration needs to be given to the rest of the loan portfolio in determining bank capital adequacy on an overall basis.

In an effort to quickly assess the effect of capital losses in the entire loan portfolio on key capital ratios, the Solver function in Microsoft Excel was used to determine the PD_p and LGD_p rates needed to bring these key ratios below the recommended ratios outlined in Table 5.11. Here, *EAD* is \$3,008,425,000 and is Pinnacle Bank's loans and leases, net of unearned income from Schedule RI-B Part II of the aforementioned Call Report. The lowest PD_p figure needed to fall below a recommended ratio is 2.013% for the Total Capital Ratio, ceteris paribus, nearly three times the PD_p calculated by the model. A similar story is seen for LGD_p where an increase to 26.924% from 15.000% is needed in order for the Total Capital Ratio to fall below recommended levels, ceteris paribus. This results in a CVaR at the 99.97% level of 2.599% or \$78,201,139.79. The other four key regulatory ratios studied all required much higher PD_p or LGD_p rates in order to fall below recommended levels. It should be noted that this is purely hypothetical and is included only to demonstrate the extremely high PD_p or LGD_p rates needed in order to deplete capital to an unsatisfactory level as defined by the FDIC when looking at the entire loan portfolio.

5.2.3 Results Using 60 Day Definition of Default

The regression results below in Table 5.12 show the model using the 60 day definition of default. The model shows us that only the leverage variable at origination is statistically significant at the 1% level using a one-sided hypothesis test, just as in the 90 day model. The repayment capacity variable is statistically significant at the 10% level using a one-sided hypothesis test, whereas it was statistically insignificant in the 90 day model. The profitability and industry variables are again statistically insignificant. Liquidity is now statistically insignificant versus being significant at the 1% level in the 90 day model. All coefficients had the expected sign.

Table 5.12: Logistic Regression Results Using 60 Days Past Due Definition of Default

Variable	Estimated Coefficient	Standard Error	z	P>|z|
Debt-to-Equity	0.723	0.151	4.790	0.000
Current Ratio	-0.053	0.089	-0.600	0.549
Capital Debt Repayment Capacity	-0.065	0.048	-1.360	0.175
Return on Equity	-0.339	0.664	-0.510	0.609
Livestock Producer	0.045	0.372	0.120	0.905
Constant	-4.543	0.407	-11.170	0.000
Goodness of Fit Statistics				
	Likelihood Ratio Chi^2	**Prob > Chi^2**	**Pseudo R^2**	
	32.779	0.000	0.102	

Given the likelihood ratio's chi-square value, the model is statistically significant in predicting loan default. As such, the null hypothesis that β_i for all independent variables is zero is rejected. However, the low pseudo R^2 suggests that the model does not include all of the variables in predicting default. This along with the lack of statistical significance in the independent variables suggests the 60 day default model is not very useful in determining PD_i.

The marginal effects of each independent variable are demonstrated below in Table 5.13. Like in the 90 day model, a one unit change in *CDRC*, *ROE*, and *COW* has little to no impact on the predicted PD_i. *D/E* has a greater impact on PD_i in the 60 day model, with a one unit change altering PD_i 1.2%. *CR* has practically no marginal effect on PD_i in the 60 day model, whereas it was the largest in the 90 day model. The marginal effect of *D/E* remains statistically significant at the 1% level. *CDRC* is significant at the 10% level. The remaining three marginal effects are all statistically insignificant, just as in the model.

Table 5.13: Marginal Effects Using 60 Days Past Due Definition of Default

Variable	Estimated Marginal Effect	Standard Error	z	P>|z|
Debt-to-Equity	0.012	0.003	3.970	0.000
Current Ratio	-0.001	0.002	-0.600	0.551
Capital Debt Repayment Capacity	-0.001	0.001	-1.340	0.182
Return on Equity	-0.006	0.011	-0.510	0.610
Livestock Producer	0.001	0.006	0.120	0.905

Again a two percent (2%) cutoff was employed to assess the model's ability to correctly predicted PD_i. These findings are summarized below in Table 5.14.

Table 5.14: Prediction Results Using 60 Days Past Due Definition of Default

	Loans Correctly Predicted (%)	Loans Correctly Predicted	Actual Loans
All Loans	82.60%	1,462	1,770
Defaulted Loans	56.25%	18	32
Non-Defaulted Loans	83.08%	1,444	1,738

PD_p, LGD_p, *EL*, *UL(α)*, and *CVAR (1-α)* are all summarized below in Tables 5.15-5.18. *EAD* and the denominators of the capital figures remain the same as in Section 5.2.1. *SD* and SD_p were calculated at 14.735% and 4.683%, respectively.

Table 5.15: Expected Loss Figures Using 60 Days Past Due Definition of Default

Portfolio Probability of Default	2.221%
Portfolio Loss Given Default	15.000%
Portfolio Expected Loss (%)[a]	0.333%
Exposure at Default	$ 997,635,000
Portfolio Expected Loss ($)[b]	$ 3,323,024.96

[a] PD_p x LGD_p = EL in percentage terms

[b] PD_p x LGD_p x EAD = EL in dollar terms

Table 5.16: Unexpected Loss Figures Using 60 Days Past Due Definition of Default

Unexpected Loss 5% (%)	1.155%
Unexpected Loss 5% ($)	$ 11,527,622.59
Unexpected Loss 1% (%)	1.634%
Unexpected Loss 1% ($)	$ 16,302,941.48
Unexpected Loss 0.03% (%)	2.411%
Unexpected Loss 0.03% ($)	$ 24,048,993.67

Table 5.17: Credit Value-at-Risk Figures Using 60 Days Past Due Definition of Default

Credit Value-at-Risk 95% (%)	1.489%
Credit Value-at-Risk 95% ($)	$ 14,850,647.55
Credit Value-at-Risk 99% (%)	1.967%
Credit Value-at-Risk 99% ($)	$ 19,625,966.44
Credit Value-at-Risk 99.97% (%)	2.744%
Credit Value-at-Risk 99.97% ($)	$ 27,372,018.63

Table 5.18: Loss Figures as % of Capital Using 60 Days Past Due Definition of Default

	As % of Total Equity Capital	As % of Tier 1 Capital
Expected Loss	0.795%	0.843%
Unexpected Loss (5%)	2.756%	2.926%
Credit Value-at-Risk (95%)	3.551%	3.769%
Unexpected Loss (1%)	3.898%	4.138%
Credit Value-at-Risk (99%)	4.693%	4.981%
Unexpected Loss (0.03%)	5.750%	6.104%
Credit Value-at-Risk (99.97%)	6.545%	6.947%

Using a 60 day definition of default, PD_p and all of the loss figures increased, as would be expected. In the most extreme case, just over 6.5% of the bank's total equity capital as of 06/30/15 is needed to backstop the bank's losses in the agricultural loan portfolio. This is nearly twice the capital needed in the 90 day model.

5.2.4 Capital Implications of Losses Using 60 Day Definition of Default

To analyze the impact of losses to key regulatory capital ratios, the *CVaR (1-α)* figures were subtracted from three capital figures, just as in Section 5.2.2. Those ratios can be seen below in Table 5.19.

Table 5.19: Loss Effects on Capital Ratios Using 60 Days Past Due Definition of Default

	Common Equity Tier 1 Capital Ratio	Tier 1 Capital Ratio	Total Capital Ratio	Tier 1 Leverage Ratio	Capital Conservation Buffer
Current	11.537%	11.537%	12.790%	9.328%	5.537%
Post-Loss (95%)	11.102%	11.102%	12.355%	8.976%	5.102%
Post-Loss (99%)	10.962%	10.962%	12.215%	8.863%	4.962%
Post-Loss (99.97%)	10.735%	10.735%	11.988%	8.680%	4.735%
Recommended	7.000%	8.500%	10.500%	≥ 5.000%	2.500%
Required	4.500%	6.000%	8.000%	4.000%	0.625%

Just as with the 90 day model, the bank appears to be well capitalized given a 60 day definition of default. All key regulatory capital ratios exceed both recommended and required figures per Basel III. Again, it should be noted that the *CVaR (1-α)* figures only cover the agricultural loan portfolio.

5.2.5 Results Using 30 Day Definition of Default

The regression results below in Table 5.20 show the model using the 30 day definition of default. The model shows us that, just as in the 60 day model, only the leverage variable at origination is statistically significant at the 1% level using a one-sided hypothesis test. No other independent variable is statistically significant. All coefficients had the expected sign.

Table 5.20: Logistic Regression Results Using 30 Days Past Due Definition of Default

Variable	Estimated Coefficient	Standard Error	z	P>|z|
Debt-to-Equity	0.312	0.089	3.510	0.000
Current Ratio	-0.021	0.020	-1.000	0.315
Capital Debt Repayment Capacity	-0.015	0.018	-0.840	0.404
Return on Equity	-0.022	0.356	-0.060	0.952
Livestock Producer	0.019	0.150	0.130	0.899
Constant	-2.180	0.153	-14.240	0.000

Goodness of Fit Statistics

Likelihood Ratio Chi^2	Prob > Chi^2	Pseudo R^2
19.196	0.002	0.015

Given the likelihood ratio's chi-square value, the model is statistically significant in predicting loan default. As such, the null hypothesis that β_i for all independent variables is zero is rejected. However, the extremely low pseudo R^2 suggests that the model does not include all of the variables in predicting default. This along with the lack of statistical significance in the independent variables suggests the 30 day default model is seemingly worthless in determining PD_i.

The marginal effects of each independent variable are demonstrated below in Table 5.21. Like the 60 day model, a one unit change in *CR*, *CDRC*, *ROE*, or *COW* has little to no impact on the predicted PD_i. *D/E*, however, has the greatest impact on PD_i in the 30 day model relative to the 90 and 60 day models, with a one unit change altering PD_i 3.2%. The marginal effect of *D/E* remains statistically significant at the 1% level. The remaining four independent variables all have statistically insignificant marginal effects.

Table 5.21: Marginal Effects Using 30 Days Past Due Definition of Default

Variable	Estimated Marginal Effect	Standard Error	z	P>|z|
Debt-to-Equity	0.032	0.009	3.510	0.000
Current Ratio	-0.002	0.002	-1.000	0.316
Capital Debt Repayment Capacity	-0.002	0.002	-0.830	0.404
Return on Equity	-0.002	0.036	-0.060	0.952
Livestock Producer	0.002	0.015	0.130	0.899

A two percent (2%) cutoff is again employed to assess the model's ability to predict PD_i. These results are summarized below in Table 5.22. The lowest PD_i calculated in the 30 day model was 3.83%, demonstrating that the 30 day model is clearly ineffective in predicting PD_i.

Table 5.22: Prediction Results Using 30 Days Past Due Definition of Default

	Loans Correctly Predicted (%)	Loans Correctly Predicted	Actual Loans
All Loans	11.75%	208	1,770
Defaulted Loans	100.00%	208	208
Non-Defaulted Loans	0.00%	0	1,562

PD_p, LGD_p, *EL*, *UL(α)*, and *CVAR (1-α)* are all summarized below in Tables 5.23-5.26. *EAD* and the denominators of the capital figures remain the same as in Sections 5.2.1 and 5.2.2. *SD* and SD_p were calculated at 32.611% and 10.364%, respectively.

Table 5.23: Expected Loss Figures Using 30 Days Past Due Definition of Default

Portfolio Probability of Default	12.099%
Portfolio Loss Given Default	15.056%
Portfolio Expected Loss (%)[a]	1.822%
Exposure at Default	$ 997,635,000
Portfolio Expected Loss ($)[b]	$ 18,172,528.34

[a]PD_p x LGD_p = EL in percentage terms

[b]PD_p x LGD_p x EAD = EL in dollar terms

Table 5.24: Unexpected Loss Figures Using 30 Days Past Due Definition of Default

Unexpected Loss 5% (%)	2.567%
Unexpected Loss 5% ($)	$ 25,607,066.74
Unexpected Loss 1% (%)	3.630%
Unexpected Loss 1% ($)	$ 36,214,796.86
Unexpected Loss 0.03% (%)	5.355%
Unexpected Loss 0.03% ($)	$ 53,421,612.40

Table 5.25: Credit Value-at-Risk Figures Using 30 Days Past Due Definition of Default

Credit Value-at-Risk 95% (%)	4.388%
Credit Value-at-Risk 95% ($)	$ 43,779,595.09
Credit Value-at-Risk 99% (%)	5.452%
Credit Value-at-Risk 99% ($)	$ 54,387,325.21
Credit Value-at-Risk 99.97% (%)	7.176%
Credit Value-at-Risk 99.97% ($)	$ 71,594,140.74

Table 5.26: Loss Figures as % of Capital Using 30 Days Past Due Definition of Default

	As % of Total Equity Capital	As % of Tier 1 Capital
Expected Loss	4.345%	4.612%
Unexpected Loss (5%)	6.123%	6.499%
Credit Value-at-Risk (95%)	10.468%	11.111%
Unexpected Loss (1%)	8.659%	9.191%
Credit Value-at-Risk (99%)	13.004%	13.803%
Unexpected Loss (0.03%)	12.773%	13.558%
Credit Value-at-Risk (99.97%)	17.118%	18.171%

As expected, PD_p and all of the loss figures increased when the 30 days past due definition of default was employed. At the 99.97% solvency rate, 17.2% of the bank's total equity capital as of 06/30/15 is needed to protect the bank's losses in the agricultural loan portfolio. This is more than four times the capital needed in the 90 day model.

5.2.6 Capital Implications of Losses Using 30 Day Definition of Default

To analyze the impact of losses to key regulatory capital ratios, the *CVaR (1-α)* figures were subtracted from three capital figures, just as in the 90 and 60 day models. Those ratios can be seen below in Table 5.27.

Table 5.27: Loss Effects on Capital Ratios Using 30 Days Past Due Definition of Default

	Common Equity Tier 1 Capital Ratio	Tier 1 Capital Ratio	Total Capital Ratio	Tier 1 Leverage Ratio	Capital Conservation Buffer
Current	11.537%	11.537%	12.790%	9.328%	5.537%
Post-Loss (95%)	10.255%	10.255%	11.508%	8.291%	4.255%
Post-Loss (99%)	9.944%	9.944%	11.197%	8.040%	3.944%
Post-Loss (99.97%)	9.441%	9.441%	10.693%	7.633%	3.441%
Recommended	7.000%	8.500%	10.500%	≥ 5.000%	2.500%
Required	4.500%	6.000%	8.000%	4.000%	0.625%

Unlike in the prior two models, the key regulatory capital ratios begin to approach the recommended ratios when losses are taken out of capital using the 30 day definition of default, namely in the total capital ratio. However, all key regulatory capital ratios still exceed both recommended and required figures per Basel III. Still, the *CVaR (1-α)* figures only cover the agricultural loan portfolio and don't take into account any potential losses in the commercial, consumer, municipal, or securities portfolios.

5.2.7 Comparative Results

In an effort to compare results of this study to other studies which covered a greater time period, the loss rates were recalculated using the PD_p ratings on agricultural loan portfolios from two other studies. This was done partially due to the concern of the limited number of default observations in Pinnacle Bank's portfolio. Katchova and Barry (2005) calculated both the historical and statistical PD rates using Illinois farm data from 1995-2002 covering 16,049 observations. Featherstone, Roessler, and Barry (2006), meanwhile, calculated an average PD rating for the Seventh Farm Credit District's portfolio on 157,853 loans during the same time period of 1995-2002. Katchova and Barry's (2005) calculated historical PD_p rate was 0.785% and the calculated statistical PD_p rate was 2.474%. Featherstone, Roessler, and Barry's (2006) calculated PD_p rate was 1.610%. Again, Pinnacle Bank's calculated PD_p rate using the 90 day definition of default was 0.682%.

Using the above described PD_p rates, CVaR at the 99.97% level was calculated at 1.448% (original), 1.561% (Katchova historical), 2.912% (Katchova statistical), and 2.300% (Featherstone). In dollar terms, these figures were \$14.4 million, \$15.6 million, \$29.0 million, and \$23.0 million, respectively. Here, PD_p as calculated in the 90 day model is the lowest of any of the four. However, current capital levels still appear more than sufficient to backstop even the losses calculated in the highest PD_p scenario.

CHAPTER VI: CONCLUSION

6.1 Summary

Loan and financial data from Pinnacle Bank's loan accounting database and lending software, respectively, were analyzed in an effort to determine the bank's agricultural loan portfolio's probability of default (PD). Ultimately, 1,770 unique observations were analyzed using a binary logit regression model and three different definitions of default: 90 days, 60 days, and 30 days past due. The 90 days past due definition proved to be somewhat useful in predicting the portfolio's PD. The 60 day definition was only marginally useful while the 30 day definition was essentially worthless.

After determining the portfolio's PD rate, expected losses (EL) and unexpected losses (UL) were calculated in both percentage and dollar terms in an effort to determine the portfolio's Credit Value-at-Risk (CVaR). CVaR was calculated at three different solvency rates: 95%, 99%, and 99.97%. The CVaR figure demonstrates the capital needed by the bank in order to backstop potential losses in the bank's agricultural loan portfolio.

Finally, the calculated CVaRs were taken from current reported capital balances in an effort to determine the adequacy of bank capital. Five key regulatory capital ratios (Common Equity Tier 1 Capital Ratio, Tier 1 Capital Ratio, Total Capital Ratio, Tier 1 Leverage Ratio, and Capital Conservation Buffer) were assessed post-loss to see how losses in the agricultural loan portfolio would affect the bank in future regulatory assessments once the full Basel III capital requirements are enacted by the FDIC. These results showed that in every instance, the bank is well capitalized and prepared to sustain losses in the agricultural loan portfolio without dipping below either the recommended or required levels of any of the five ratios.

6.2 Limitations

There were several limitations in this study. One of the largest limitations was the size and scope of the loan data. The loans included in the sample were only those active as of early July 2015. Thus, any loan paid off prior to January 1, 2015 was not available for analysis. This caused the number of observed defaults to be very low. Moreover, the number of defaults was further limited due to the fact that the time period from which loan data was available was a relatively strong period for agriculture in Nebraska, Kansas, and Missouri. Also, only those loans that could be paired with financial data were included in the dataset. Not all of the bank's branches appear to fully utilize the bank's lending software and as such, their loans were not included in the dataset. Because of this fact, losses were calculated at three other PD rates presented by other studies.

Profitability and repayment capacity (one half of the financial ratios used as independent variables in the model) were shown to be statistically insignificant, no matter the definition of default. This is assumed to be due to the fact that the lending software used by the bank does not allow for average figures to be downloaded from the point of loan origination. These two items are typically accessed by lenders, underwriters, and credit analysts on an average basis as well as multi-year trends. A particularly poor year, for instance, may have caused a typically strong producer who is highly unlikely to default to borrow funds without largely affecting their overall leverage or liquidity. If average figures were able to be employed, it likely would still show the producer having strong repayment and profitability ratios at origination and helped to improve the statistical significance of these two measures in the model.

6.3 Recommendations

Using a 90 day definition of default (consistent with Basel requirements), the bank currently appears to be well capitalized in the event of losses in the agricultural loan portfolio. After subtracting predicted losses from the bank's current capital, the bank's capital appears adequate when measured using five key regulatory capital ratios. As such, it does not appear as if management needs to retain further capital solely for the purpose of protecting the bank against potential losses from agricultural loans.

Also, increasing the capabilities of the loan accounting and lending software packages could help to improve the effectiveness of future studies such as this. The ability to cover more loans would help to include loans that have defaulted and been paid or charged off prior to the timeframe in which loan data is pulled from. Improving the interactions of the two software packages would also limit the need for manual manipulation of the data, thereby increasing the ease and effectiveness of conducting future analysis while lessening the chance for manual errors and oversight.

6.4 Future Research

This thesis only covered losses to the agricultural loan portfolio. To give management a complete and thorough analysis of the adequacy of bank capital, future research needs to assess the PD and loss rates for the bank's entire portfolio. Only then would management truly be able to assess the adequacy of bank capital.

Loss given default (LGD) was not specifically calculated for the portfolio due to limited availability of loss information. Future research should attempt to calculate LGD for senior, collateralized loans in order to improve the accuracy of predicted losses.

Future research should also expand the definition of default. While the 90 days past due definition is consistent with Basel III requirements, expanding default definitions to include bankruptcies, notes placed on non-accrual, and notes with charge-offs should increase not only the number of default observations, but also the accuracy of calculating PD.

Assessing the bank's current internal risk rating system relative to its ability to predict borrower default could also be assessed in future research. Doing so may not only improve the model by including assessments of subjective measures of a borrower's creditworthiness (e.g., character and management ability), it may also allow the bank to test the effectiveness of its risk rating system.

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